

Article

Multi-Criteria Evaluation of Bioavailable Trace Elements in Fine and Coarse Particulate Matter: Implications for Sustainable Air-Quality Management and Health Risk Assessment

Elwira Zajusz-Zubek ^{1,*}  and Zygmunt Korban ²
¹ Department of Air Protection, Faculty of Energy and Environmental Engineering, The Silesian University of Technology, Konarskiego 22B, 44-100 Gliwice, Poland

² Department of Safety Engineering, Faculty of Mining, Safety Engineering and Industrial Automation, Silesian University of Technology, Akademicka 2, 44-100 Gliwice, Poland; zygmunt.korban@polsl.pl

* Correspondence: elwira.zajusz-zubek@polsl.pl

Abstract

Bioavailable fractions of particulate-bound trace elements are key determinants of inhalation toxicity, yet air-quality assessments typically rely on total metal concentrations, which may underestimate health risks. This study integrates the exchangeable (F1) and reducible (F2) fractions of trace elements in fine (PM_{2.5}) and coarse (PM₁₀) particulate matter with multi-criteria decision-making (TOPSIS) and similarity-based classification (Czekanowski's method). Archival weekly-integrated samples from the summer season were collected at eight industrially influenced sites in southern Poland. Sequential extraction (F1–F2) and ICP-MS were applied to quantify concentrations of cadmium, cobalt, chromium, nickel, and lead in PM_{2.5} and PM₁₀. Aggregated hazard values were then derived with TOPSIS, and site similarity was explored using Czekanowski's reordered distance matrices. Regulatory targets for cadmium and nickel, and the limit for lead in PM₁₀ were not exceeded, but F1/F2 profiles revealed pronounced site-to-site differences in potential mobility that were not evident from total concentrations. Rankings were consistent across size fractions, with site *P*₁ exhibiting the lowest hazard indices and *P*₈ the highest, while mid-rank sites formed reproducible similarity clusters. The proposed chemical-fractionation and multivariate framework provides a reproducible screening tool for multi-element exposure, complementing compliance checks and supporting prioritisation of sites for targeted investigation and environmental management. In the sustainability context, bioavailability-based indicators strengthen air-quality assessment by linking monitoring data with health-relevant and cost-effective management strategies, supporting efficient resource allocation and reducing exposure in vulnerable populations.

Keywords: PM_{2.5}; PM₁₀; trace elements; sequential extraction; F1–F2 fractions; bioavailable fractions; TOPSIS; Czekanowski's method; multi-criteria decision-making; sustainable air-quality management



Academic Editor: Konstantinos Dimitriou

Received: 9 September 2025

Revised: 2 October 2025

Accepted: 10 October 2025

Published: 13 October 2025

Citation: Zajusz-Zubek, E.; Korban, Z. Multi-Criteria Evaluation of Bioavailable Trace Elements in Fine and Coarse Particulate Matter: Implications for Sustainable Air-Quality Management and Health Risk Assessment. *Sustainability* **2025**, *17*, 9045. <https://doi.org/10.3390/su17209045>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Particulate matter (PM), particularly fine (PM_{2.5}) and coarse (PM₁₀) fractions, constitutes a major class of ambient air pollutants, with well-documented negative impacts on human health and climate change, including direct radiative forcing, altered cloud formation, and intensified climate warming. Within these particles, bioavailable trace

elements represent particularly hazardous constituents, posing significant health risks due to their toxicity and environmental persistence.

A WHO-supported meta-analysis of 106 cohorts reported a 9.5% increase in all-cause mortality per $10 \mu\text{g}\cdot\text{m}^{-3}$ $\text{PM}_{2.5}$ [1]. In the EU-27, approximately 253,000 premature deaths in 2021 were linked to $\text{PM}_{2.5}$ above the $5 \mu\text{g}\cdot\text{m}^{-3}$ WHO guideline [2], and emerging evidence suggests a $\geq 14\%$ higher dementia risk with chronic $\text{PM}_{2.5}$ exposure [3]. Together with associations to asthma, COPD, cardiovascular disease, lung cancer, diabetes, and premature death [4], this underscores the substantial health burden of PM. Although PM_{10} is less represented in long-term cohorts [4], it has been linked to respiratory mortality and pro-inflammatory airway responses, particularly in regions with resuspended coarse dust [5–7]. Climate change projections indicate that rising temperatures may amplify PM concentrations and associated health burdens [8].

The concentration and composition of PM are shaped by a complex interplay of natural and anthropogenic sources, meteorological conditions, and regional transport [9,10]. Exceedances of regulatory limits for PM_{10} and $\text{PM}_{2.5}$ result not only from direct emissions but also from the atmospheric formation of secondary particles from gaseous precursors such as SO_2 , NO_x , NH_3 , and volatile organic compounds [11]. The chemical, physical, and biological properties of PM—rather than mass concentration alone—are now recognized as key determinants of its health effects [12].

Because such health impacts depend not only on particle mass but also on chemical form, we next focus on the bioavailability and speciation of trace elements—proximate drivers of inhalation toxicity and health risks.

Among the chemical constituents of PM, trace metals and metalloids are of particular concern due to their persistence, non-biodegradability, bioaccumulation potential, and toxicity [13,14]. Elements such as lead (Pb), cadmium (Cd), arsenic (As), and nickel (Ni) enter the atmosphere through fossil fuel combustion, industrial processes, traffic emissions, and long-range transport [15,16]. Importantly, the health risks posed by these metals depend on their chemical speciation and bioavailability, rather than merely their total concentrations [17,18]. Only bioavailable forms—those mobilizable and absorbable by living organisms—directly induce toxicological effects [19,20]. Therefore, total metal concentrations alone may not adequately predict health risks.

Sequential extraction procedures have become standard methods for operationally defining trace metal mobility and bioavailability in PM, partitioning them into ion-exchangeable (F1) and carbonate/oxide-bound (F2) fractions [21,22]. Due to their high mobility and chemical reactivity under physiologically relevant conditions, these fractions pose a significantly greater direct risk to human health compared to metals bound in more stable geochemical matrices. The exchangeable (F1) fraction comprises water-soluble and weakly surface-bound species readily mobilized under neutral physiological conditions, such as those encountered in airway surface fluids. The carbonate/oxide-bound (F2) fraction consists of metals associated predominantly with carbonates and amorphous iron/manganese oxides, which dissolve under mildly acidic or reducing conditions (approximately pH 5–6), characteristic of lung fluids, atmospheric droplets, or polluted precipitation. Recent studies confirm the sensitivity of F1 and F2 fractions to environmental variations in pH and redox potential, highlighting their ecological and health risk relevance [21,22].

Significant knowledge gaps persist, notably the lack of harmonized protocols for sequential extraction, limiting comparability across studies and regions [23]. Most air quality monitoring and risk assessments still rely on total metal concentrations, potentially underestimating risks associated with bioavailable fractions [20]. Moreover, data on the spatial and temporal variability of mobile forms of carcinogenic and toxic elements in PM remain scarce, particularly outside Europe and North America [24]. Given the global

variability in PM composition and limited integrated bioavailability data from numerous regions, this study provides essential comparative insights relevant to international air quality standards and health risk assessment guidelines.

To address PM composition complexity and associated health risks, recent studies have increasingly employed multivariate methods, such as TOPSIS [25], clustering approaches (e.g., hierarchical clustering, k-means), and factor/dimensionality-reduction techniques such as principal component analysis (PCA) [26]. These methods integrate multiple parameters—such as toxic element concentrations, source profiles, and environmental variables—into synthetic indicators, enhancing air quality and risk assessments. However, multivariate techniques are rarely applied to chemically fractionated PM data, especially bioavailable metal forms. Despite PCA and clustering being successfully applied [26], and bioaccessibility being assessed *in vitro* [27], few studies integrate these approaches. This methodological gap underscores the need for integrated frameworks that combine chemically defined fractions with multivariate evaluation schemes for accurate and policy-relevant air quality management [28].

This study introduces an innovative approach that integrates the operationally defined exchangeable (F1) and reducible (F2) fractions of trace elements in PM_{2.5} and PM₁₀—proxies for bioavailability—with advanced multi-criteria decision-making (TOPSIS) and similarity-based classification (Czekanowski's method).

2. Materials and Methods

2.1. Study Area and Archival Data Source

This study analyses archival datasets collected at eight sites in southern Poland situated near industrial sources including coal-fired power plants and coking plants. Sampling was conducted exclusively in summer to minimize the influence of the heating season, particularly low-stack residential emissions (near-ground releases from domestic coal/wood stoves and small boilers) that are widespread in Poland. Four weekly 7-day sessions per site were performed. Particulate matter was sampled at 1.5 m above ground level using a Dekati® PM₁₀ cascade impactor at 1.8 m³·h^{−1}, which segregates particles into <1 µm, 1–2.5 µm, 2.5–10 µm, and >10 µm aerodynamic ranges. The present analysis focuses on PM_{2.5} and PM₁₀ only. Sites P1–P8, located in the vicinity of coal-fired power plants and coking facilities, are shown in Figure 1; site-level input concentrations used in subsequent analysis are compiled in Table 1 (PM_{2.5}) and Table 2 (PM₁₀). The sampling design and regional context are consistent with the authors' previous applications to ambient PM and with the archival monograph documenting the underlying dataset collected in the non-heating season [29–33].

Polycarbonate filters (Nuclepore, Whatman International Ltd., Maidstone, UK) were used for impactor stages >1 µm, and Teflon filters (Pall International Ltd., New York, NY, USA) for the <1 µm stage, in accordance with instrument specifications. Although different filter materials were used for different particle size ranges, both filter types were validated for trace metals recovery and yielded comparable extraction efficiencies under the applied sequential extraction protocol [29–33]. Each weekly sampling session yielded one integrated sample per stage and site. Material collected at each stage was processed independently through the complete extraction and ICP-MS workflow; no pooling across weeks was performed. For PM_{2.5}, air volume-normalised concentrations from the <1 µm and 1–2.5 µm stages were summed after analysis to derive site-level values for each chemical fraction (F1 and F2). For PM₁₀, concentrations from the <1 µm, 1–2.5 µm, and 2.5–10 µm stages were similarly summed post-analysis [29–33].

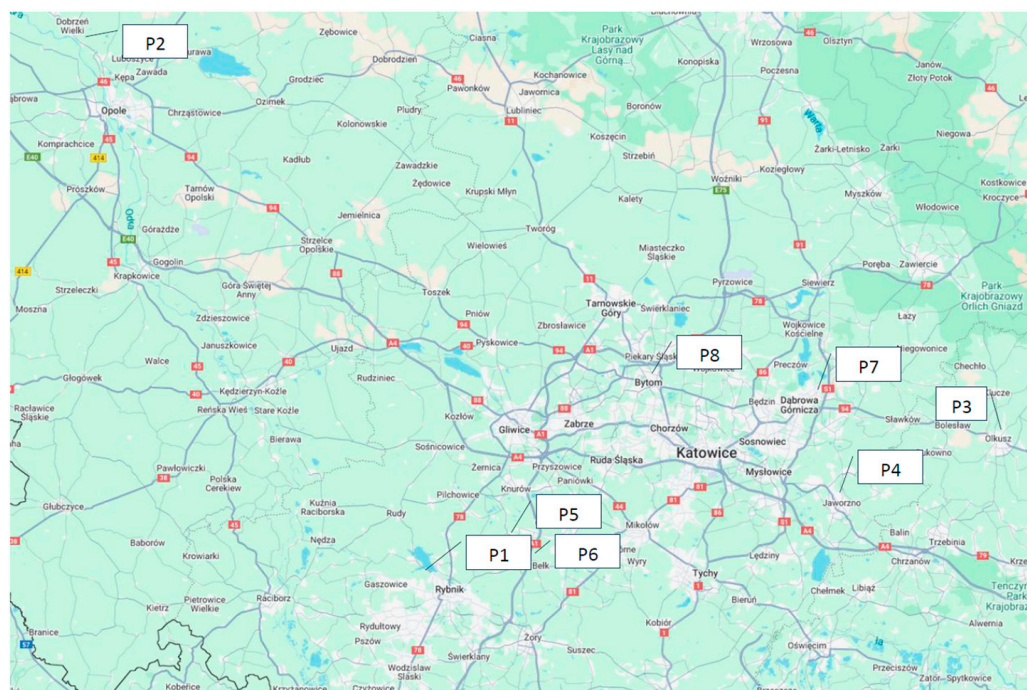


Figure 1. Location of sampling sites (base map from <http://mapa-google.pl/polska>) (accessed on 12 September 2025). Source: Authors' own elaboration.

Table 1. Average concentrations of trace elements in fractions F1 and F2 in PM_{2.5}.

Fraction	Measurement Point	Concentration of Trace Elements, ng/m ³				
		Cd	Co	Cr	Ni	Pb
F1	P ₁	0.1590	0.0181	0.1770	0.2040	3.0400
	P ₂	0.2380	0.0192	0.1620	0.1820	3.5300
	P ₃	0.4390	0.0169	0.3900	0.2370	8.8100
	P ₄	0.7050	0.0229	0.4080	0.2630	10.6000
	P ₅	0.4450	0.0273	0.1870	0.8030	8.4000
	P ₆	0.3850	0.0421	0.3600	0.3710	6.9200
	P ₇	0.9900	0.0306	0.3090	0.5400	15.1000
	P ₈	2.1500	0.0565	0.6390	0.3870	39.1000
F2	P ₁	0.0566	0.0092	0.4400	0.0529	4.1200
	P ₂	0.0772	0.0092	0.4410	0.0611	7.0000
	P ₃	0.0968	0.0107	0.1030	0.2460	8.9300
	P ₄	0.1510	0.0092	0.0944	0.0656	9.3400
	P ₅	0.1070	0.0073	0.4930	0.1900	8.2100
	P ₆	0.0782	0.0124	0.5060	0.1160	7.9600
	P ₇	0.1940	0.0084	0.5430	0.1040	18.9000
	P ₈	0.5950	0.0227	0.5470	0.1250	72.6000

Table 2. Average concentrations of trace elements in fractions F1 and F2 in PM₁₀.

Fraction	Measurement Point	Concentration of Trace Elements, ng/m ³				
		Cd	Co	Cr	Ni	Pb
F1	P ₁	0.1660	0.0232	0.1890	0.2210	3.0700
	P ₂	0.2460	0.0232	0.1740	0.2050	3.5600
	P ₃	0.4840	0.0221	0.4270	0.2590	8.9000
	P ₄	0.7190	0.0279	0.4210	0.2820	10.6000
	P ₅	0.4680	0.0369	0.2030	0.8380	8.4700
	P ₆	0.4060	0.0505	0.2070	0.4070	6.9700
	P ₇	1.0700	0.0384	0.3470	0.6200	15.2000
	P ₈	2.3100	0.0725	0.6900	0.4310	39.5000
F2	P ₁	0.0717	0.0145	0.6610	0.0717	5.0200
	P ₂	0.1240	0.0177	0.6620	0.1160	8.7400
	P ₃	0.1490	0.0153	0.1500	0.2850	12.5000
	P ₄	0.2030	0.0183	0.1420	0.1190	11.3000
	P ₅	0.1250	0.0155	0.7400	0.2370	10.5000
	P ₆	0.1020	0.0263	0.7590	0.1840	9.7300
	P ₇	0.3540	0.0209	0.8150	0.2180	26.5000
	P ₈	0.9600	0.0552	0.8210	0.2350	10.4000

2.2. Chemical Fractionation F1–F2 and ICP-MS Analysis

Sequential extraction targeted two operationally defined fractions: F1 (highly mobile, water-soluble/exchangeable; 15 mL ultrapure water, 3 h mixing at room temperature) and F2 (potentially mobile under reducing conditions, bound to carbonates and metal oxides; 10 mL NH₂OH·HCl 0.25 M, 5 h mixing). This protocol followed a previously validated methodology developed by the authors [29–33]. Extracts were filtered at 0.45 µm prior to quantification. Five trace elements of toxicological relevance (Cd, Co, Cr, Ni, Pb) were analysed by ICP-MS (NexION 300D, PerkinElmer Inc., Waltham, MA, USA). Calibration employed a CertPUR multi-element ICP-MS standard (Merck KGaA, Darmstadt, Germany). Analytical accuracy was confirmed using ERM-CZ120 (European Commission, Joint Research Centre, Geel, Belgium) and NIST SRM 1648a (National Institute of Standards and Technology, Gaithersburg, MD, USA), yielding recoveries between 94–108%. Each batch included procedural blanks; detection limits (LoD) ranged from 0.01–0.1 µg·L^{−1}, depending on the element. Analytical precision (RSD) was below 5%. Values below LoD were imputed as LoD/2 for descriptive statistics and multi-criteria decision analysis (MCDM). Although different filter materials were used across impactor stages, both were validated for trace metal recovery, and no material-dependent correction factors were required.

Elements present in the F1 fraction (highly mobile, water-soluble) and in the F2 fraction (potentially mobile under reducing conditions, associated with carbonates and metal oxides) may contribute to toxicity and—when mobilized—become bioaccessible (and potentially bioavailable), which can lead to adverse health effects. The carcinogenic risk (Excess Lifetime Cancer Risk, ELCR) associated with trace elements at monitoring sites P₁–P₈ for these mobile forms in PM_{2.5} and PM₁₀, together with the underlying mathematical model, is presented in reference [33]. In the present study, we use F1/F2 within multi-criteria indices (TOPSIS) as a screening-level assessment aligned with inhalation bioaccessibility, complementing compliance checks based on total concentrations.

2.3. Data Analysis and Classification Methods

In the broadly understood assessment process, so-called synthetic measures play a significant role. These measures are determined using methods for solving multi-attribute decision-making (MADM) problems. These methods enable the construction of scalar values (synthetic evaluation indicators) by incorporating numerical values of criteria and the differentiation of assigned weights. The derived measures allow for the replacement of an entire set of features describing an object (criteria, parameters, partial evaluations) with a single variable representing an aggregated quantity. Among the methods used in solving multi-attribute decision-making (MADM) problems, the following can be distinguished, among others [34–36]:

- Additive methods, in which a matrix of normalized evaluations is determined, and the selection is made based on the variant (object) with the highest total score. This group of methods includes, among others: the Simple Additive Weighting (SAW) Method and the Fuzzy Simple Additive Weighting (F-SAW) Method, which, as a modification of SAW, employs fuzzy numbers.
- Analytical hierarchy methods and related approaches, in which independent criteria and variants (objects) are compared in pairs. This enables the creation of a scale vector and the ranking of variants. Examples of methods in this group include: Analytical Hierarchy Process (AHP), Analytic Network Process (ANP) (a development of AHP), and Ratio Estimation in Magnitudes or deciBells to Rate Alternatives which are Non-Dominated (REMBRANDT).
- Verbal methods, which are primarily based on qualitative parameters for which an objective aggregation model cannot be developed. Examples of verbal methods include ZAPROS and ZAPROS III.
- ELECTRE family methods (ELECTRE I, ELECTRE IV, ELECTRE III), in which variants (objects) are evaluated based on criteria to be maximized. Each criterion is assigned a positive weight, a concordance coefficient is determined, and the condition of non-discordance is verified. The final result is an outranking relation and a dependency graph between the objects.
- PROMETHEE methods (PROMETHEE I, PROMETHEE II, PROMETHEE II + veto, EXtension of the PROMETHEE method—EXPROM), in which objects (variants) are compared in pairs based on the adopted evaluation criteria. Preference functions are determined, and indifference and strict preference thresholds are defined. For each pair of objects (variants), preference flows are calculated.

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was applied in the manuscript. Alongside the Development Measure Method, Višekriterijumska Optimizacija i Kompromisno Resenje (VIKOR), and Decision-Making Trial and Evaluation Laboratory (DEMATEL), it belongs to the group of methods utilizing reference points. In this group, objects (variants) are compared against abstract reference solutions (in the case of TOPSIS: the “ideal” and “anti-ideal” solutions). Subsequently, for each object (variant), the distance to the reference solution(s) is determined.

As part of the calculations, “subjective” weights/evaluation criteria were assigned to each trace-element concentration value. Unlike “objective” weights determined by mathematical procedures (e.g., the Shannon-entropy-based method), the approach used in this article reflects the preferences of the evaluators (the authors). Specifically, we adopted an equal-weighting scheme (all criteria set to 1.0 for Cd, Co, Cr, Ni, and Pb) to reflect a screening-level design, to avoid bias from uncertain toxicity scaling across size fractions, and to keep the F1/F2 mobility signal transparent and reproducible. The absence of differential weighting across criteria was a deliberate choice. Alternative objective or

toxicity-informed weights (e.g., entropy-based, REL/RfC-based) can be explored in future sensitivity analyses.

Using the TOPSIS method, the measurement sites (points P_1 to P_8) were treated as *objects* in a multidimensional space, where each coordinate j corresponds to the concentration of a given trace metal (cadmium, cobalt, chromium, nickel, and lead). These objects are compared against weighted reference solutions: the positive ideal solution vector (pattern) and the negative ideal solution vector (antipattern) [34,37–44]. The relationship between the coordinates of the pattern and the antipattern is shown in Equations (1) and (2), respectively:

$$z_{0j}^+ = \begin{cases} \max_i \{z_{ij}\} & \text{for stimulant variables} \\ \min_i \{z_{ij}\} & \text{for destimulant variables} \end{cases} \quad (1)$$

$$z_{0j}^- = \begin{cases} \min_i \{z_{ij}\} & \text{for stimulant variables} \\ \max_i \{z_{ij}\} & \text{for destimulant variables} \end{cases} \quad (2)$$

where: z_{ij} —variable/parameter/coordinate after normalization.

In order to evaluate each object and facilitate its comparison with other objects, Euclidean distances were calculated between the vector representing the object's image and the positive ideal vector d_{i0}^+ (Equation (3)), and between the object and the negative ideal vector d_{i0}^- (Equation (4)) [34,37–44]:

$$d_{i0}^+ = \sqrt{\sum_{j=1}^m (z_{ij} - z_{0j}^+)^2}, \quad (3)$$

$$d_{i0}^- = \sqrt{\sum_{j=1}^m (z_{ij} - z_{0j}^-)^2}, \quad (4)$$

The best *object* is defined as the one for which its value vector has both the shortest distance from the positive ideal vector and the longest distance from the negative ideal vector.

The second method used in the manuscript is the Czekanowski method (also known as Czekanowski's diagram or the diagraphical Czekanowski's method). It is a universal statistical classification method.

In Czekanowski's method, the rows and corresponding columns of matrix D are reordered so that the smallest distance values—representing the most similar objects—are positioned as close to the diagonal as possible. With increasing distance from the diagonal, the values of the distance measures progressively increase (Equation (5)) [45–47].

$$D = |d_{rs}|, \text{ dla } r, s = 1, 2, \dots, n \quad (5)$$

where:

d_{rs} —the distance between the r -th and s -th objects;

n —number of objects.

Whereas the TOPSIS method involves calculating Euclidean distances between each object vector and both the ideal and anti-ideal solution vectors, Czekanowski's method computes distances between the objects themselves.

All distance measures are divided into several classes, each assigned a graphical symbol. It should be noted that in Czekanowski's method, the degree of fit is influenced by various subjective factors, such as the assumed average difference between the analyzed objects. The requirement for maximum concentration of objects along the main diago-

nal can only be achieved through successive approximations. As the final outcome of applying Czekanowski's method, a so-called ordered distance matrix between objects is obtained. The resulting linear ordering of classified objects enables the identification of clusters—groups of objects located close to each other in multidimensional space.

In the example presented in the manuscript, the MaCzek v. 3.0 program was used [48]. This application operates in the Windows system (Windows 95 and later) and allows for the creation of diagrams for up to 250 objects and 100 descriptive features per object.

The final results obtained using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) may differ, even when based on an identical set of input variables, due to the potential subjectivity involved in defining the weight vector W , which reflects the evaluator's preferences.

In the case of Czekanowski's method, the outcome of the object-ordering procedure—and the decision to accept a given arrangement as final—also depends on the preferences of the analyst. The adopted graphical elements (e.g., symbols and colours) facilitate a visual evaluation of the reordered distance matrix D , which in turn supports the decision of when to terminate the iterative row and column rearrangement process.

3. Results and Discussion

The air sampling locations/measurement points/objects P_1 to P_8 were considered in two different ways:

- in the case of determining the aggregated hazard values for trace elements contained in the mobile fraction F1, collected through inhalation with PM_{2.5} and PM₁₀, considering them as points in a five-dimensional space ($j \in \langle 1;5 \rangle$), where: $j = 1$ corresponds to cadmium concentration, $j = 2$ to cobalt concentration, $j = 3$ to chromium concentration, $j = 4$ to nickel concentration, and $j = 5$ to lead concentration.
- in the case of determining the aggregated hazard values and considering them, together with the average concentration of trace elements in fractions F1 and F2, as points in a ten-dimensional space ($j \in \langle 1;10 \rangle$), where: $j = 1$ corresponds to the concentration of cadmium in fraction F1, $j = 2$ to the concentration of cobalt in fraction F1, $j = 3$ to the concentration of chromium in fraction F1, $j = 4$ to the concentration of nickel in fraction F1, $j = 5$ to the concentration of lead in fraction F1, $j = 6$ to the concentration of cadmium in fraction F2, $j = 7$ to the concentration of cobalt in fraction F2, $j = 8$ to the concentration of chromium in fraction F2, $j = 9$ to the concentration of nickel in fraction F2, and $j = 10$ to the concentration of lead in fraction F2.

The input data for calculating the aggregated hazard values using the TOPSIS method are presented in Tables 1 and 2.

The analysis of trace element concentrations in fractions F1 and F2 revealed that the lowest concentration was observed for *object* P_1 :

- cadmium:
 - 0.1590 ng/m³ in the F1 fraction of PM_{2.5};
 - 0.0566 ng/m³ in the F2 fraction of PM_{2.5};
 - 0.1660 ng/m³ in the F1 fraction of PM₁₀;
 - 0.0717 ng/m³ in the F2 fraction of PM₁₀;
- cobalt:
 - 0.0145 ng/m³ in the F2 fraction of PM₁₀;
- nickel:
 - 0.0529 ng/m³ in the F2 fraction of PM_{2.5};
 - 0.0717 ng/m³ in the F2 fraction of PM₁₀;

- lead:
 - 3.0400 ng/m³ in the F1 fraction of PM_{2.5};
 - 4.1200 ng/m³ in the F2 fraction of PM_{2.5};
 - 3.0700 ng/m³ in the F1 fraction of PM₁₀;
 - 5.0200 ng/m³ in the F2 fraction of PM₁₀.

The lowest concentration of Co in the F1 fractions of PM_{2.5} and PM₁₀ was recorded at *object* P₃, with values of 0.0169 ng/m³ and 0.0221 ng/m³, respectively. In contrast, the lowest concentration of Ni in the F1 fractions of PM_{2.5} and PM₁₀ was observed at *object* P₂, with values of 0.182 ng/m³ and 0.2050 ng/m³, respectively.

The highest concentrations of trace elements were most frequently measured at *object* P₈. However, exceptions were noted for the concentrations of Ni in the F1 and F2 fractions of PM_{2.5} and PM₁₀, as well as for Pb in the F2 fraction of PM₁₀.

In the vicinity of the eight studied sites, no exceedances of the target levels for Cd, Pb, and Ni or the permissible level for Pb in PM₁₀ were recorded [4]. Assessment against regulatory targets cannot be performed for trace elements in PM_{2.5} because Polish legislation does not specify target values for this size fraction. Nonetheless, regulatory compliance does not imply absence of health-relevant concern: the exchangeable (F1) and reducible (F2) fractions revealed site-specific mobility patterns indicative of inhalation bioaccessibility and potential toxicity. This highlights the added value of our approach, since bioavailable fractions may pose risks even below legal thresholds. To address this, we applied TOPSIS to integrate multi-element F1/F2 data into aggregated hazard indices, which consistently ranked sites from lowest to highest concern, thereby providing a reproducible screening framework that complements compliance checks. Taken together, these findings underscore that assessments based on total concentrations may underestimate potential risks, because the bioavailable fractions (F1 and F2) represent mobilizable fractions more directly relevant to inhalation exposure and toxicity. Accordingly, incorporating F1/F2 into multi-criteria indices provides a screening-level perspective that complements (rather than replaces) compliance checks based on total concentrations.

The determined values q_i represent aggregated/synthetic values, based on which it can be concluded that *object* P₁ was the best rated. This *object* was characterized by the highest values of the aggregated variable, considering the concentrations of the abovementioned trace elements in the F1 fraction of PM_{2.5} and PM₁₀ ($q_1 = 0.9805$ and $q_1 = 0.9847$, respectively), as well as when considering the combined F1 and F2 fractions of PM₁₀ ($q_1 = 0.8657$).

Similarly to the single-criterion assessments (which involved analyzing the concentrations of individual elements in the atmosphere separately), the worst results in the multicriteria evaluation were also observed for *objects* P₅, P₇, and (especially) P₈. Site P₈, with the lowest value of q_8 among the diagnosed sites, ranked last in all the partial rankings (see Tables 3 and 4):

- $q_8 = 0.2133$ in the F1 fraction of PM_{2.5};
- $q_8 = 0.2018$ for the combined F1 and F2 fractions in PM_{2.5};
- $q_8 = 0.1949$ for the F1 fraction in PM₁₀;
- $q_8 = 0.2404$ for the combined F1 and F2 fractions in PM₁₀.

Table 3. Ranking of *objects* for the F1 and F2 fractions in PM_{2.5}.

Ranking of <i>Objects</i> for the F1 Fraction			Ranking of <i>Objects</i> (for the F1 and F2 Fractions)		
No.	<i>Object Number i</i>	q_i	No.	<i>Object Number i</i>	q_i
1	1	0.9805	1	1	0.8693

Table 3. Cont.

Ranking of Objects for the F1 Fraction			Ranking of Objects (for the F1 and F2 Fractions)		
No.	Object Number i	q_i	No.	Object Number i	q_i
2	2	0.9703	2	2	0.8636
3	3	0.8048	3	4	0.8010
4	4	0.7374	4	6	0.7431
5	6	0.7347	5	3	0.7399
6	5	0.6613	6	5	0.6858
7	7	0.6038	7	7	0.6506
8	8	0.2133	8	8	0.2018

Table 4. Ranking of objects for the F1 and F2 fractions in PM₁₀.

Ranking of Objects for the F1 Fraction			Ranking of Objects (for the F1 and F2 Fractions)		
No.	Object Number i	q_i	No.	Object Number i	q_i
1	1	0.9847	1	1	0.8657
2	2	0.9767	2	2	0.8449
3	3	0.7948	3	4	0.7795
4	6	0.7829	4	3	0.7471
5	4	0.7480	5	6	0.7375
6	5	0.6739	6	5	0.6811
7	7	0.5948	7	7	0.5360
8	8	0.1949	8	8	0.2404

To identify similar sites, the authors of the manuscript propose using a method of multicriteria assessment (the Czekanowski method), in which *objects* are compared with each other (see Figures 2 and 3).

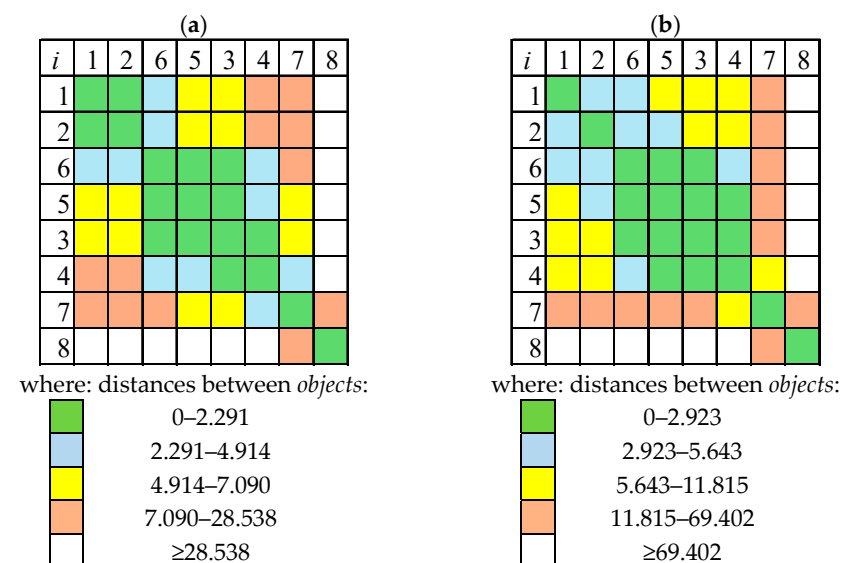


Figure 2. Czekanowski's diagram—grouping of *objects* based on the concentration of trace elements: (a) in the F1 fraction of PM_{2.5}; (b) in the F1 and F2 fractions of PM_{2.5}. Source: Own elaboration.

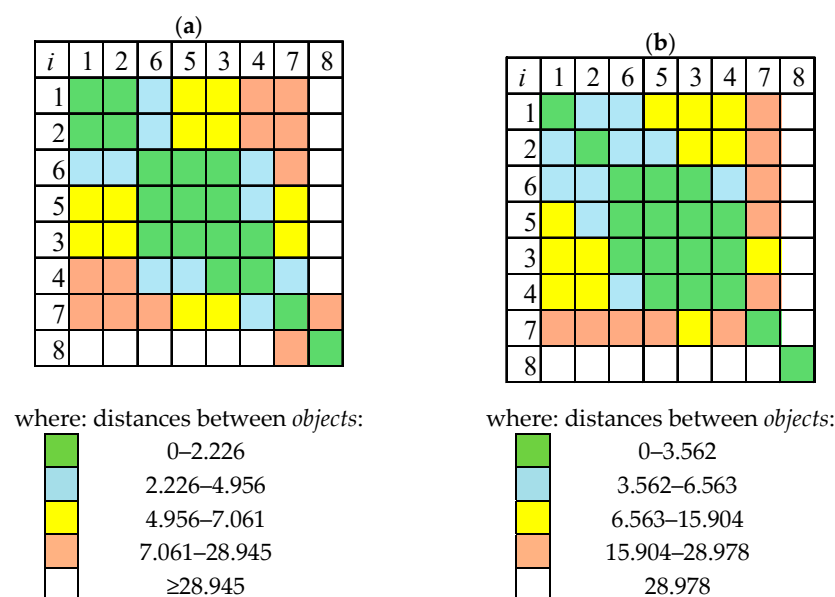


Figure 3. Czekanowski's diagram—grouping of objects based on the concentration of trace elements: (a) in the F1 fraction of PM_{10} ; (b) in the F1 and F2 fractions of PM_{10} . Source: Own elaboration.

The application of Czekanowski's method for grouping *objects* based on the concentrations of trace elements in the F1 and F2 fractions of $PM_{2.5}$ revealed the following:

- For the F1 fraction in $PM_{2.5}$, three subsets characterized by the highest similarity of elements/*objects* could be identified: $\{P_1; P_2\}$, $\{P_3; P_5; P_6\}$, and $\{P_3; P_4\}$, where the distances between objects did not exceed 2.291. Considering an increased distance of up to 4.914 between objects P_1 and P_6 , P_2 and P_6 , P_5 and P_4 , and P_6 and P_4 the resulting sets were $\{P_1; P_2; P_6\}$ and $\{P_3; P_4; P_5; P_6\}$;
- When considering the F1 and F2 fractions together in $PM_{2.5}$, two subsets with the highest similarity of elements/*objects* could be identified: $\{P_3; P_5; P_6\}$ and $\{P_3; P_4; P_5\}$, with distances between *objects* not exceeding 2.923. If the distance between objects P_6 and P_4 increased to 5.643, a single subset of the most similar objects was observed: $\{P_3; P_4; P_5; P_6\}$.

This suggests that, for instance, in the case of an *object* located in an area where the average concentrations of cadmium, cobalt, chromium, nickel, and lead in the F1 fraction were recorded as 0.1590 ng/m³, 0.0181 ng/m³, 0.1770 ng/m³, 0.2040 ng/m³, and 3.0400 ng/m³, respectively (*object* P_1), and another *object* in a region where the corresponding average concentrations of these elements were 0.2380 ng/m³, 0.0192 ng/m³, 0.1620 ng/m³, 0.1820 ng/m³, and 3.5300 ng/m³ (values characterizing *object* P_2), a similar or comparable risk associated with the combined/simultaneous impact of carcinogenic elements on human health was observed.

A similar approach can be applied to group *objects* based on the concentrations of trace elements in the F1 and F2 fractions of PM_{10} :

- When evaluating the content of the F1 fraction, three subsets characterized by the highest similarity of elements/*objects* could be identified: $\{P_1; P_2\}$, $\{P_3; P_5; P_6\}$, and $\{P_3; P_4\}$, with distances between *objects* not exceeding 2.226. Here as well, increasing the distances between *objects*, P_1 and P_6 , P_2 and P_6 , P_5 and P_4 , and P_6 and P_4 , up to 4.956 resulted in the formation of the following groups: $\{P_1; P_2; P_6\}$ and $\{P_3; P_4; P_5; P_6\}$;
- When considering the F1 and F2 fractions together in PM_{10} , two three-element subsets could be distinguished: $\{P_3; P_4; P_5\}$ and $\{P_3; P_5; P_6\}$, where the distances between *objects* did not exceed 3.562. Allowing for greater distances between *objects* P_4 and P_6 (up to 6.563) yielded a single four-element subset: $\{P_3; P_4; P_5; P_6\}$.

To place our findings in context, the measured concentrations of particulate-bound trace elements in $PM_{2.5}$ and PM_{10} are broadly consistent in order of magnitude with ranges recently reported for Polish urban/industrial sites [49,50] and with pan-European datasets [51]. We also note that datasets resolving the exchangeable (F1) and reducible (F2) fractions remain scarce in both Europe and Asia [22,52]. Recent Asian studies [27,53]—for example, Hotan, China [27]—report general ranges that overlap with those observed in urban/industrial settings, providing contextual benchmarks for pollution levels and health-relevant risk assessments, while regional source mixes and methodological differences may lead to site-specific deviations.

In this context, our study introduces an innovative approach that integrates the operationally defined exchangeable (F1) and reducible (F2) fractions of trace elements in $PM_{2.5}$ and PM_{10} —proxies for bioavailability—with advanced multi-criteria decision-making (TOPSIS) and similarity-based classification (Czekanowski's method). This speciation-informed, multi-criteria framework provides a reproducible screening layer that links mobility to health-relevant hazard rankings and site similarity, complementing compliance checks and guiding the prioritization of locations and elements for follow-up dose-based quantitative health risk assessment.

Because sampling was restricted to summer to minimize low-stack residential emissions, our findings reflect warm-season conditions. Multi-season campaigns (autumn–winter–spring) are planned to verify rank stability and characterize seasonal variability in F1/F2 profiles.

The results of trace element concentration measurements were undoubtedly influenced by the location of the monitoring sites themselves: the character of the area (rural or urban environment), proximity to industrial plants (coking plants, power stations), and atmospheric conditions.

Specifically:

- Site P_1 was located in a suburban area of the Silesian Voivodeship, in the vicinity of an operating power plant with a capacity of 1775 MW; population: 2300.
- Site P_2 was located in a rural area of the Opole Voivodeship near an operating power plant with a capacity of 1492 MW; population: 520.
- Site P_3 was also located in a rural area, in the Małopolskie Voivodeship, near an operating power plant with a capacity of 786 MW; population: 700.
- Site P_4 was located in the suburbs of a city in the Silesian Voivodeship, in the immediate vicinity of a power plant with a capacity of 1345 MW; population: 95,500.
- Site P_5 was located in a suburban area of the Silesian Voivodeship, in the immediate vicinity of a coking plant; population: 27,300.
- Site P_6 was located in a small suburban district (population: 3300) of a city in the Silesian Voivodeship, surrounded by a small operating coking plant.
- Site P_7 was also located in a small suburban district (population: 700) of a city in the Silesian Voivodeship, in the vicinity of a large coking plant.
- Site P_8 was located on the outskirts of a large city in the Silesian Voivodeship (population: 174,700), in the immediate vicinity of a coking plant. The 45-chamber coke battery, built after World War II, is still in operation, with a current production capacity of up to 250,000 tons of coke per year (heating coke, blast furnace coke, low-phosphorus coke, foundry coke, and small coke).

Measurements and detailed analyses of meteorological conditions (wind speed and direction, etc.) were not carried out. At present, the use of the mobile laboratory of the Silesian University of Technology is planned in this regard.

4. Conclusions

The study employed advanced analytical techniques and mathematical modelling methods to evaluate air quality, with a particular focus on particulate matter (PM) and its associated trace elements, especially their chemically defined bioavailable forms, which are key determinants of inhalation toxicity and environmental mobility. Applying multicriteria comparative methods (TOPSIS and Czekanowski's method) allowed a thorough examination and classification of locations based on air-quality indicators and highlighted significant differences in the mobility and potential bioavailability of selected trace elements.

Environmental measurements presented in this research revealed no exceedances of WHO standards or permissible levels established by Polish legislation for PM₁₀, respirable PM_{2.5}, and associated trace elements (Cd, Co, Cr, Ni, and Pb). However, the adopted methodological framework provided deeper insights compared to standard compliance checks based solely on total metal concentrations. Using operationally defined fractions (exchangeable F1 and reducible F2), distinct site-specific differences in element mobility were identified, offering a more nuanced perspective on potential health risks.

The applied scalar multicriteria techniques effectively facilitated processing extensive datasets describing anthropogenic impacts, demonstrating their utility in effectively ranking and classifying locations according to air-quality parameters. Such synthetic indicators constitute valuable complements—rather than substitutes—to traditional air-quality assessment frameworks, enabling simultaneous consideration of multiple pollutants and factors influencing environmental health.

Beyond its screening function, the speciation-informed, multi-criteria framework provides actionable guidance for air-quality management. Sites with elevated TOPSIS hazard indices (e.g., P_8) should be prioritized for enhanced, multi-season monitoring (including simulated-lung-fluid bioaccessibility tests), and for targeted source-oriented audits at nearby industrial facilities (e.g., capture efficiency, enclosure of emission points, fugitive-dust control, housekeeping). Similarity clusters can support regional coordination by identifying municipalities with comparable source profiles and enabling joint interventions and resource sharing. Incorporating F1/F2-based indicators as trigger metrics in local air-quality plans would align monitoring with health-relevant risk, complement compliance checks based on total concentrations, and help prioritize cost-effective emission-reduction measures and risk communication for vulnerable groups.

A critical methodological gap remains in assessing the toxicity and bioavailability of particulate-bound trace elements exclusively from total concentrations. Future research should integrate biological assays (e.g., lung-fluid simulations, oxidative potential assessments) with multicriteria decision-making frameworks to better understand the actual health risks posed by airborne pollutants.

This study builds upon the authors' previous work, confirming the analytical robustness and environmental significance of fractions F1 and F2 as indicators for evaluating mobility and toxicity. Recent international research further supports combining chemical fractionation and multivariate statistical methods to enhance the predictive accuracy and ecological relevance of particulate matter analyses.

In conclusion, integrating chemically defined fractions with advanced statistical approaches provides a reproducible, scalable method for assessing air quality and prioritizing management actions. Such an integrated approach is recommended for supporting environmental decision-making, informing public health policies, and identifying areas requiring more detailed investigation or remediation.

Author Contributions: Conceptualization, E.Z.-Z. and Z.K.; methodology, E.Z.-Z.; software, Z.K.; validation, E.Z.-Z. and Z.K.; formal analysis, E.Z.-Z. and Z.K.; investigation, E.Z.-Z.; resources, E.Z.-Z. and Z.K.; data curation, E.Z.-Z.; writing—original draft preparation, E.Z.-Z. and Z.K.; writing—review and editing, E.Z.-Z. and Z.K.; visualization, Z.K.; supervision, E.Z.-Z. and Z.K.; project administration, E.Z.-Z.; funding acquisition, E.Z.-Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Faculty of Energy and Environmental Engineering, Silesian University of Technology (statutory research).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Orellano, P.; Kasdagli, M.-I.; Pérez Velasco, R.; Samoli, E. Long-Term Exposure to Particulate Matter and Mortality: An Update of the WHO Global Air Quality Guidelines Systematic Review and Meta-Analysis. *Int. J. Public Health* **2024**, *69*, 1607683. [CrossRef] [PubMed]
- Soares, J.; Plass, D.; Kienzler, S.; González Ortiz, A.; Gsell, A.; Horálek, J. Health Risk Assessment of Air Pollution: Assessing the Environmental Burden of Disease in Europe in 2021 (ETC HE Report 2023/7, Version 2). European Topic Centre on Human Health and the Environment. Available online: <https://www.eionet.europa.eu/etcs/etc-he/products/etc-he-reports/etc-he-report-2023-7-health-risk-assessment-of-air-pollution-assessing-the-environmental-burden-of-disease-in-europe-in-2021> (accessed on 7 March 2024).
- Groenewold, M.M.; Samet, J.M.; Burnett, R.T.; Cohen, A.J.; Lim, S.S. A Systematic Review with a Burden-of-Proof Meta-Analysis of Long-Term PM_{2.5} Exposure and Dementia Risk. *Nat. Aging* **2025**, *5*, 112–120. [CrossRef]
- Paplińska-Goryca, M.; Misiukiewicz-Stepien, P.; Proboszcz, M.; Nejman-Gryz, P.; Górka, K.; Zajusz-Zubek, E.; Krenke, R. Interactions of nasal epithelium with macrophages and dendritic cells variously alter urban PM-induced inflammation in healthy, asthma and COPD. *Sci. Rep.* **2021**, *11*, 13259. [CrossRef]
- World Health Organization (WHO). *WHO Global Air Quality Guidelines: Particulate Matter (PM_{2.5} and PM₁₀), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*; WHO: Geneva, Switzerland, 2021; Available online: <https://www.who.int/publications/i/item/9789240034228> (accessed on 14 August 2025).
- Joshi, D.C.; Negi, P.; Devi, S.; Lohani, H.; Kumar, R.; Gupta, M.; Ming, L.C. Fine Particulate Matter (PM_{2.5}, PM₁₀): A Silent Catalyst for Chronic Lung Diseases in India; A Comprehensive Review. *Environ. Chall.* **2025**, *20*, 101215. [CrossRef]
- Adly, H.M.; Saleh, S.A.K. Long-Term Trends in PM₁₀, PM_{2.5}, and Trace Elements in Ambient Air: Environmental and Health Risks from 2020 to 2024. *Atmosphere* **2025**, *16*, 415. [CrossRef]
- Leão, M.L.P.; Zhang, L.; da Silva Júnior, F.M.R. Effect of Particulate Matter (PM_{2.5} and PM₁₀) on Health Indicators: Climate Change Scenarios in a Brazilian Metropolis. *Environ. Geochem. Health* **2023**, *45*, 2229–2240. [CrossRef] [PubMed]
- Francová, H.; Chrastný, V.; Vítková, M.; Šillerová, H.; Komárek, M. Health Risk Assessment of Metal(loid)s in Soil and Particulate Matter from Industrialized Regions: A Multidisciplinary Approach. *Environ. Pollut.* **2020**, *260*, 114057. [CrossRef]
- Angyal, A.; Szoboszlai, Z.; Major, I.; Molnár, M.; Varga, T.; Török, Z.; Papp, E.; Enikő, F.; Gini, M.; Manousakas, M.I.; et al. Characterisation of Urban Aerosol Size Distribution by Radiocarbon and PIXE Analyses in a Middle-European Urban Environment for Source Identification: A Pilot Study. *Environ. Sci. Pollut. Res.* **2024**, *31*, 47258–47274. [CrossRef]
- Jimenez, J.L.; Canagaratna, M.R.; Donahue, N.M.; Prevot, A.S.H.; Zhang, Q.; Kroll, J.H.; DeCarlo, P.F.; Allan, J.D.; Coe, H.; Ng, N.L.; et al. Evolution of organic aerosols in the atmosphere. *Science* **2009**, *326*, 1525–1529. [CrossRef]
- Li, T.; Yu, Y.; Sun, Z.; Duan, J. A comprehensive understanding of ambient particulate matter and its components on the adverse health effects based from epidemiological and laboratory evidence. *Part. Fibre Toxicol.* **2022**, *19*, 67. [CrossRef]
- Matei, E.; Răpă, M.; Mates, I.M.; Popescu, A.-F.; Bădiceanu, A.; Balint, A.I.; Covaliu-Mierlă, C.I. Heavy Metals in Particulate Matter—Trends and Impacts on Environment. *Molecules* **2025**, *30*, 1455. [CrossRef]
- Liao, K.; Zhang, J.; Chen, Y.; Lu, X.; Fung, J.C.H.; Ying, Q.; Yu, J.Z. Regional Source Apportionment of Trace Metals in Fine Particulate Matter Using an Observation-Constrained Hybrid Model. *Npj Clim. Atmos. Sci.* **2023**, *6*, 65. [CrossRef]

15. Ondrasek, G.; Shepherd, J.; Rathod, S.; Dharavath, R.; Rashid, M.I.; Brtnicky, M.; Shahid, M.S.; Horvatinec, J.; Rengel, Z. Metal Contamination—A Global Environmental Issue: Sources, Implications & Advances in Mitigation. *RSC Adv.* **2025**, *15*, 3904–3927. [CrossRef]
16. World Health Organization (WHO). *Human Health Effects of Benzene, Arsenic, Cadmium, Nickel, Lead and Mercury in Ambient Air*; WHO Regional Office for Europe: Copenhagen, Denmark, 2024; Available online: <https://iris.who.int/handle/10665/375606> (accessed on 14 August 2025).
17. Sah, D.; Verma, P.K.; Kumari, K.M.; Lakhani, A. Chemical Fractionation of Heavy Metals in Fine Particulate Matter and Their Health Risk Assessment through Inhalation Exposure Pathway. *Environ. Geochem. Health* **2019**, *41*, 1445–1458. [CrossRef] [PubMed]
18. Tiwari, R.; Botle, A.; Rajouriya, K.; Singh, P.P.; Taneja, A. Chemical Fraction and Health Effect of Size Segregate PM at National Highway of Northern India. *Pollution* **2023**, *9*, 1671–1685. [CrossRef]
19. Expósito, A.; Markiv, B.; Santibáñez, M.; Fadel, M.; Ledoux, F.; Courcot, D.; Fernández-Olmo, I. Ascorbate Oxidation Driven by PM_{2.5}-Bound Metal(oid)s Extracted in an Acidic Simulated Lung Fluid in Relation to Their Bioaccessibility. *Air Qual. Atmos. Health* **2024**, *17*, 177–189. [CrossRef]
20. Xie, J.-J.; Yuan, C.-G.; Xie, J.; Shen, Y.-W.; He, K.-Q.; Zhang, K.-G. Speciation and Bioaccessibility of Heavy Metals in PM_{2.5} in Baoding City, China. *Environ. Pollut.* **2019**, *252*, 1468–1476. [CrossRef]
21. Conca, E.; Malandrino, M.; Giacomino, A.; Abollino, O.; Traversi, R.; Giardi, F.; Becagli, S. Chemical Fractionation of Trace Elements in Arctic PM₁₀ Samples. *Atmosphere* **2021**, *12*, 1152. [CrossRef]
22. Świetlik, R.; Trojanowska, M. Chemical Fractionation in Environmental Studies of Potentially Toxic Particulate-Bound Elements in Urban Air: A Critical Review. *Toxics* **2022**, *10*, 124. [CrossRef] [PubMed]
23. Rajouriya, K.; Pipal, A.S.; Taneja, A. A Review on Sequential Extraction of Metals Bound Particulate Matter and Their Health Risk Assessment. *J. Atmos. Chem.* **2024**, *81*, 145–162. [CrossRef]
24. Nirmalkar, J.; Lee, K.; Ahn, J.; Lee, J.; Song, M. Comparisons of Spatial and Temporal Variations in PM_{2.5}-Bound Trace Elements in Urban and Rural Areas of South Korea, and Associated Potential Health Risks. *Atmosphere* **2023**, *14*, 753. [CrossRef]
25. Das, P.; Biswas, A.; Nayak, S.; Misra, S. A Fuzzy TOPSIS Framework for Assessment of Air Quality Index Values Across Different Stations—A Case Study on Kolkata in India. *J. Sci. Res.* **2025**, *17*, 519–529. [CrossRef]
26. Nuchdang, S.; Kingkam, W.; Tippawan, U.; Sriwiang, W.; Fungklin, R.; Rattanaphra, D. Metal Composition and Source Identification of PM_{2.5} and PM₁₀ at a Suburban Site in Pathum Thani, Thailand. *Atmosphere* **2023**, *14*, 659. [CrossRef]
27. Liu, B.; Zhang, Y.; Talifu, D.; Ding, X.; Wang, X.; Abulizi, A.; Zhao, Q.; Zhang, X.; Zhang, R. In Vitro Bioaccessibility and Health Risk of Heavy Metals from PM_{2.5}/PM₁₀ in Arid Areas—Hotan City, China. *Atmosphere* **2023**, *14*, 1066. [CrossRef]
28. Ogwu, M.C.; Izah, S.C.; Sawyer, W.E.; Amabie, T. Environmental Risk Assessment of Trace Metal Pollution: A Statistical Perspective. *Environ. Geochem. Health* **2025**, *47*, 94. [CrossRef]
29. Zajusz-Zubek, E.; Kaczmarek, K.; Mainka, A. Trace Elements Speciation of Submicron Particulate Matter (PM₁) Collected in the Surroundings of Power Plants. *Int. J. Environ. Res. Public Health* **2015**, *12*, 13085–13103. [CrossRef]
30. Zajusz-Zubek, E.; Radko, T.; Mainka, A. Fractionation of Trace Elements and Human Health Risk of Submicron Particulate Matter (PM₁) Collected in the Surroundings of Coking Plants. *Environ. Monit. Assess.* **2017**, *189*, 389. [CrossRef]
31. Zajusz-Zubek, E.; Mainka, A.; Kaczmarek, K. Determination of Water-Soluble Elements in PM_{2.5}, PM₁₀, and PM_{2.5–10} Collected in the Surroundings of Power Plants. *E3S Web Conf.* **2018**, *28*, 01042. [CrossRef]
32. Zajusz-Zubek, E.; Korban, Z. The Use of Multi-Criteria Method in the Process of Threat Assessment to the Environment. *Sci. Rep.* **2021**, *11*, 18296. [CrossRef]
33. Zajusz-Zubek, E. *Evaluation of Forms in Which Occur Selected Trace Elements in Suspended Dust (PM₁₀) and Respirable Fraction (PM_{2.5}) in the Surroundings of Coal-Fired Power Plants and Coking Plants in the Non-Heating Season*; Silesian University of Technology Press: Gliwice, Poland, 2016. (In Polish)
34. Nermend, K. *Metody Analizy Wielokryterialnej I Wielowymiarowej We Wspomaganiu Decyzji*; PWN: Warszawa, Poland, 2017. (In Polish)
35. Nowak, M. Preference and veto thresholds in multicriteria analysis based on stochastic dominance. *Eur. J. Oper. Res.* **2004**, *158*, 339–350. [CrossRef]
36. Roy, B.; Bouyssou, D. *Aide Multicritère à la Décision: Méthodes et Cas*; Economica: Paris, France, 1993.
37. Behzadian, M.; Otaghsara, S.K.; Yazdani, M.; Ignatius, J. A state-of-the-art survey of TOPSIS applications. *Expert Syst. Appl.* **2012**, *39*, 13051–13069. [CrossRef]
38. Boran, F.E.; Genc, S.; Kurt, M.; Akay, D. A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Syst. Appl.* **2009**, *36*, 11363–11368. [CrossRef]
39. Chen, C.T. Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets Syst.* **2000**, *114*, 1–9. [CrossRef]

40. Dymova, L.; Sevastjanov, P.; Tikhonenko, A. A direct interval extension of TOPSIS method. *Expert Syst. Appl.* **2013**, *40*, 4841–4847. [CrossRef]
41. Roszkowska, E.; Kacprzak, D. The fuzzy SAW and fuzzy TOPSIS procedures based on ordered fuzzy numbers. *Inf. Sci.* **2016**, *369*, 564–584. [CrossRef]
42. Shih, H.S.; Shyur, H.J.; Lee, E.S. An extension of TOPSIS for group decision making. *Math. Comput. Model.* **2007**, *45*, 801–813. [CrossRef]
43. Wang, T.C.; Chang, T.H. Application of TOPSIS in evaluating initial training aircraft under a fuzzy environment. *Expert Syst. Appl.* **2007**, *33*, 870–880. [CrossRef]
44. Yazdi, M.M. TOPSIS Method for Multiple-Criteria Decision Making (MCDM). R Package Topsis. Available online: <https://cran.r-project.org/web/packages/topsis> (accessed on 31 July 2025).
45. Czekanowski, J. On the Differential Diagnosis of the Neanderthal Group. *Korresp. Der Dtsch. Ges. Für Anthropol. Ethnol. Und Urgesch.* **1909**, *XL*, 44–47. (In German)
46. Czekanowski, J. The Similarity Method in Application to Psychometric Research. *Badania Psychol.* **1926**, *3*, 1–40. (In Polish)
47. Jaskulski, P.; Sołtysiak, A. Diagram Czekanowskiego. Pomysł, historia, zastosowania. Klasyfikacja i analiza danych—Teoria i zastosowania. *Taksonomia 11 Pr. Nauk. Akad. Ekon.* **2004**, *1022*, 374–383. (In Polish)
48. Jaskulski, P. *MaCzek 3.0: User Manual*; Department of Anthropology, University of Warsaw: Warsaw, Poland, 2010; Available online: http://www.antropologia.uw.edu.pl/MaCzek/manual_30_pl.pdf (accessed on 8 July 2022). (In Polish)
49. Siudek, P. Chemical Composition and Source Apportionment of Ambient PM_{2.5} in a Coastal Urban Area, Northern Poland. *Chemosphere* **2024**, *356*, 141850. [CrossRef] [PubMed]
50. Reizer, M.; Calzolari, G.; Maciejewska, K.; Orza, J.A.G.; Carraresi, L.; Lucarelli, F.; Juda-Rezler, K. Measurement Report: Receptor Modeling for Source Identification of Urban Fine and Coarse Particulate Matter Using Hourly Elemental Composition. *Atmos. Chem. Phys.* **2021**, *21*, 14471–14492. [CrossRef]
51. Liu, X.; Zhang, X.; Wang, T.; Jin, B.; Wu, L.; Lara, R.; Monge, M.; Reche, C.; Jaffrezo, J.-L.; Uzu, G.; et al. PM₁₀-Bound Trace Elements in Pan-European Urban Atmosphere. *Environ. Res.* **2024**, *260*, 119630. [CrossRef]
52. Novo-Quiza, N.; Sánchez-Piñero, J.; Moreda-Piñero, J.; Turnes-Carou, I.; Muniategui-Lorenzo, S.; López, P. Oxidative potential of the inhalation bioaccessible fraction of PM₁₀ and bioaccessible concentrations of polycyclic aromatic hydrocarbons and metal(oid)s in PM₁₀. *Environ. Sci. Pollut. Res.* **2024**, *31*, 31862–31877. [CrossRef] [PubMed]
53. Sun, S.; Zheng, N.; Wang, S.; Li, Y.; Hou, S.; An, Q.; Chen, C.; Li, X.; Ji, Y.; Li, P. Inhalation Bioaccessibility and Risk Assessment of Metals in PM_{2.5} Based on a Multiple-Path Particle Dosimetry Model in the Smelting District of Northeast China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 8915. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.